Improving Crop Models: Incorporating New Processes, New Approaches, and Better Calibrations

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Introduction

Early ancestors of crop simulation models (De Wit, 1965; Monteith, 1965; Duncan et al., 1967) were born before primitive personal computers were available (e.g. Apple II released in 1977, IBM PC released in 1981). Paleo-computer programs were run in mainframes with the support of punch cards. As computers became more available and powerful, crop models evolved into sophisticated tools summarizing our understanding of how crops operate. This evolution was triggered by the need to answer new scientific questions and improve the accuracy of model simulations, especially under limiting conditions.

Crop model improvement received a significant boost with the AgMIP (*Agricultural Model Intercomparison and Improvement Project*) Project. AgMIP (Rosenzweig et al., 2013) has promoted and facilitated a systematic model intercomparison for selected crops at the global level. Pilot studies for wheat, maize, and rice have congregated ensembles of 27, 23, and 13 models respectively. Each one of these pilot studies used field information from four sentinel sites characterizing environmental and management conditions representative of important crop growing areas. As a result, various strategies for model improvement have been developed.

Model improvement involves either incorporating the simulation of processes that were not previously being considered, including alternative procedures to enhance or complement the simulation of processes already represented, or simply the use of new datasets to reveal and fix specific conditions causing model weaknesses. In the next paragraphs I will discuss these alternatives, illustrating with examples, and highlighting the need to support field experimentation and data sharing to improve crop model performance.

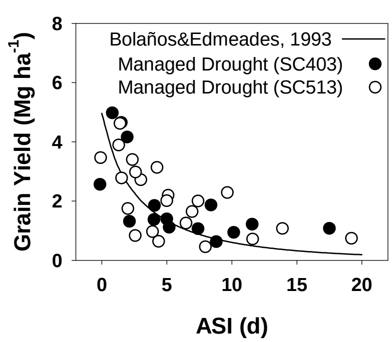

Figure 1. Relationship between grain yield and anthesis-silking interval (ASI) in maize as determined by Bolaños and Edmeades (1993). Same relationship evaluated in field studies with controlled drought around silking for two popular southern African varieties (Kindie Tesfaye, personal communication).

Incorporating New Processes

Our models are representations deliberately simplified of the cropping system. Model developers decide, depending on the model purpose, what processes to include. However, model purposes evolve as knowledge progresses and new questions arise. For instance, early models were not much concerned with the effect of elevated CO_2 on crop growth and transpiration. Abiotic stresses received attention only after the simulation of non-stress conditions was satisfactory. An example of a new process being incorporated into a maize simulation model, CERES-Maize, follows.

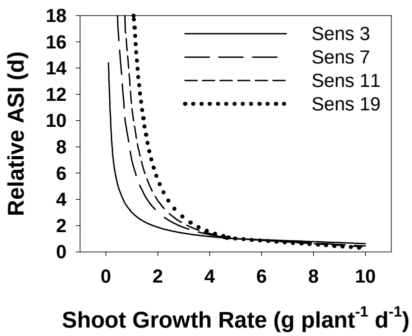

Figure 2. Simulated relative anthesis-silking interval (ASI) as a function of the average shoot growth rate during the critical period around silking. Under stress (SGR < 5 g plant^{-1} d^{-1}) calculated ASI will depend on the cultivar specific sensitivity (SENS).

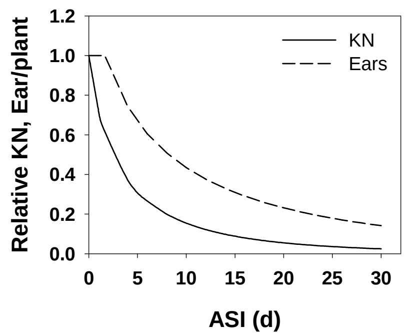

Figure 3. Simulated relative kernel number (KN) and plant barrenness (Ear plant^{-1}) as a function of the anthesis-silking interval (ASI) according to Bolaños and Edmeades (1993).

Drought and other stresses occurring around flowering in maize delay the turgor-dependent silk extrusion with negligible effect on anthesis date. This extended anthesis-silking interval (ASI) has been shown to have a serious impact on grain yield (Fig. 1). Thus the stress effects on ASI are a major target for crop breeding. Many maize models however, such as CERES-Maize, consider silking as the event defining flowering. CERES-Maize was modified to use anthesis (50% male flowering) as the cardinal event for flowering and silking (50% female flowering) will be determined by the simulated ASI, which may be delayed by stresses. The new model estimates the delayed ASI as a function of the average shoot growth rate during a critical thermal time window around anthesis. The model also accommodates different cultivar sensitivities to stresses (Fig. 2). As ASI extends, the onset of the linear grain filling delays (not shown), the plant kernel number decreases, and plant barrenness escalates (Fig. 3).
A limited evaluation of the new model indicated a good performance (Fig. 4). Two new cultivar coefficients describe ASI determined under non-stress conditions, and the sensitivity of the cultivar to stresses. Both coefficients would describe the progress of genetic improvement.

Incorporating New Approaches

Under field conditions, usually maize kernel set is limited by the source of assimilates. Therefore, many models simulate grain numbers as a function of plant growth rate,

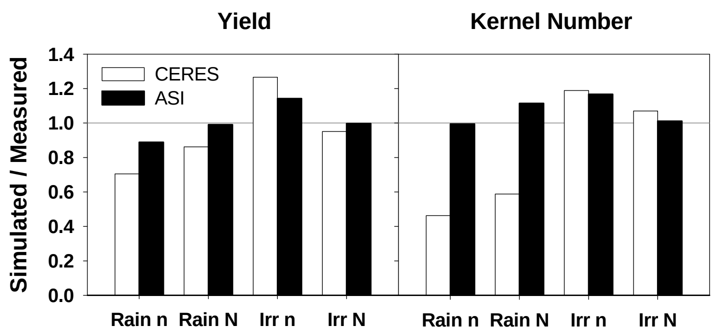

Figure 4. Relative simulations of maize grain yield and kernel number per plant obtained with CERES-Maize and with a modified version including estimated anthesis-silking interval (ASI) in response to stresses. Treatments shown are distributed with DSSAT v4.5 experiment UFGA82: Rainfed low N (Rain n), Rainfed high N (Rain N), Irrigated low N (Irr n), and Irrigated high N (Irr N).

photosynthetic rate, rate of intercepted light or a similar variable averaged over a critical period around flowering (Fig. 5). However, male and female flowering asynchrony caused by stresses, or limited pollen production around silking, may result in restricted pollination. Under these conditions, kernel set becomes sink limited, hence field dynamics of pollen shed and silk emergence should be described.

Representing either pollen or silk dynamics involved the description of processes at the population level and at the individual plant level. The model keeps account of the daily number of plants starting to shed pollen and starting to have visible silks. On the male side, daily pollen rates (pollen grain cm^{-2}) are calculated from the tassel total pollen yield and the duration of pollen shed per tassel. On the female side, daily number of receptive silks (silks ha^{-1}) are calculated by adding the newly emerged silks and the unpollinated old silks, assuming a silk remains receptive up to 6 days. Newly emerged silks are calculated from the number of silks per ear, and the corresponding duration of silk exsertion.

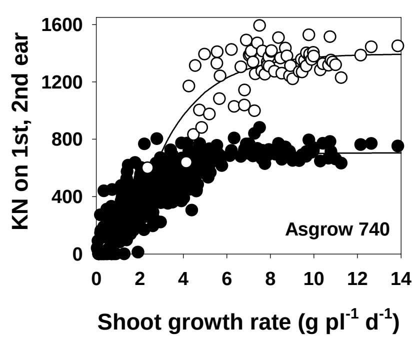

Figure 5. Field measured kernel numbers (KN) as a function of average plant growth during a 4-week critical period around flowering (Lizaso et al., 2011).

Bassetti and Westgate (1994) relationship allowed coupling daily receptive silks and pollen rates estimating a daily kernel set. These authors found that field measured pollen rates under 100 grains cm^{-2} restricted kernel set. Seasonal kernel numbers result from the accumulated daily kernel set (Fig. 6).

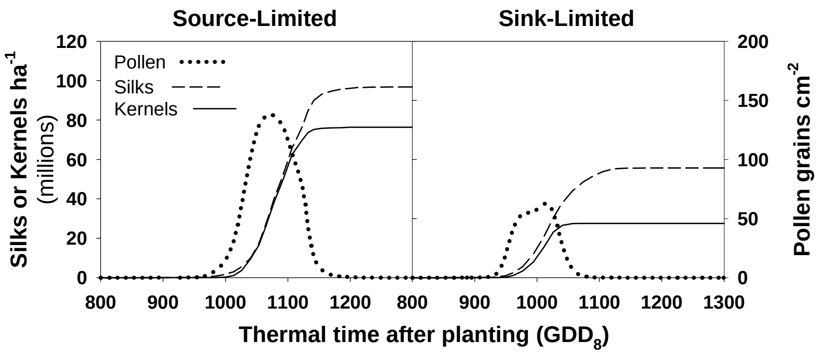

Figure 6. Simulated kernel set under source-limited and sink-limited conditions (Lizaso et al., 2007). Timing and amount of silk emergence and pollen shed were simulated daily and kernel set calculated according to Bassetti and Westgate (1994).

A modified version of CERES-Maize, including an improved source-limited simulation and the described sink-limited kernel set was compared to the official CERES-Maize, distributed with DSSAT v3.5. The new model, combining source-limited and sink-limited kernel set, reduced the mean square deviation (MSD, Gauch et al., 2003) by 64% when compared to CERES-Maize v3.5, using a measured pool of 127 fields including a range of source- and sink-limited conditions (Fig. 7).

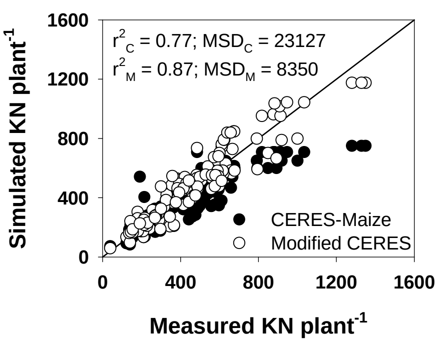

Figure 7. Simulated and measured kernel number per plant under a range of source- and sink-limited conditions. Simulations were obtained with CERES-Maize v3.5 (C) and with a modified version (M) including source-limited and sink-limited kernel set (Lizaso et al., 2007).

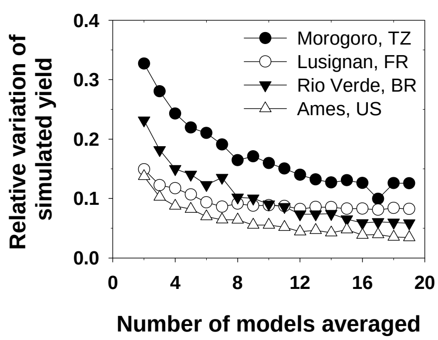

Figure 8. Relative variation between observed and average of simulated yields with n randomly chosen models from a total of 19 available at four sites. Care was taken to not repeat models in a set, and that all models were equally represented in the 210 sets (Bassu et al., 2014).

Towards the future: The need for quality and diversity of datasets

There are a number of systematic efforts with the goal of improving our current crop models. Besides the wheat, maize, and rice pilot studies of the AgMIP Project already mentioned, ongoing work by teams on sugarcane, potato, sorghum-millet, peanut, and soybean could be cited. Another large Project "advancing crop modelling for improved assessment of climate change impacts on food security" is MACSUR (*Modelling European Agriculture with Climate Change for Food Security*). MACSUR uses crops, including pastures, livestock, and trade models to address the impacts of climate change on European agricultural sector.

A particular case of model improvement is the AgMIP's Maize Model Improvement Group. The approach is to address one process at a time. A global maize expert panel meets through video conference and discuss current knowledge and recent literature on specific physiological mechanisms. Then, participants outline how contrasting models simulate that component. Alternative methodologies are tested using relevant datasets provided by participants. Meetings on phenology, leaf expansion, root water uptake, and leaf assimilation and transpiration coupling have been held. As a result, a new maize model, AgMaize, is under development.

Another important avenue for model improvement is the systematic work developed by scientists involved with model packages, such as DSSAT, APSIM, CropSyst, STICS, EPIC, and others. In a recent DSSAT Workshop gathering model developers the agenda moved across areas as different as initializing soil organic matter fractions, crop failure due to stresses, energy balance in the canopy, or cardinal temperatures, in addition to work on individual models (sunflower, cassava, maize, forages, wheat, and others).

Beyond the number of processes being included, and the approach chosen to simulate each process, a permanent concern for crop model improvement is the quality and diversity of datasets used for model calibration. Comprehensive information from field experiments many times becomes the bottleneck of model testing and calibration. If new processes are to be included in our models, quality experimental data should support these improvements. Unfortunately, quality datasets many times proceed from similar environments and crop growing conditions. Models evolve and new hypothesis are implemented and linked. Modularity of current models facilitate the exchange of code, and with it, new components can be easily examined. However, algorithms need to be parameterized and simulated responses usually require tuning some coefficients to reduce the bias with measurements. And it is not surprising that calibrated models reproduce better those environments and type of cultivars where field information was available for calibration.

The AgMIP maize pilot team showed that an ensemble of 23 crop models was able to accurately simulate grain yield across four sites, with limited information on crop and soil for parameter adjustment (Bassu et al., 2014). Adding additional input information reduced variability, but did not improve the accuracy of simulations. The ensemble of models was superior to any individual model. So, how many models are good enough? Fig. 8 from Bassu et al (2014) explores this question. First, 210 groups of two models were randomly chosen avoiding model repetition, and guaranteeing similar model representation across groups. Later, groups of three, four, and up to 19 models were formed. The absolute difference between observed and average simulated yield was calculated for each group of n models. Mean and standard deviation of the 210 differences for each of the n ensembles were computed and divided by the experimental observation yielding an estimate of relative variation. Fig. 8 indicates that as the ensemble size increased the relative variation declined differently for each site. Ensembles of 7-8 models reduced most of the variation in the US and France sites (42 and 46º N Latitude). The sites in Brazil (18º S), and in Tanzania (7º S) exhibited the largest variation with ensembles of small size, and required some 16 models to level off the relative variation. These trends provide evidence on the need for better information from tropical environments and cultivars for model calibration.

Conclusions

Model improvement is expected to continue resulting from emerging new questions, better knowledge of physiological mechanisms and cropping systems, and higher accuracy standards. International Projects of global or regional scope with multidisciplinary teams and agendas of high level goals will continue pushing for better crop simulation models. Decision making and policy makers are expected to rely on, and manage uncertainty better, assisted by more integrated simulation tools. In any case, field experimentation should continue providing support for crop model improvement.

Acknowledgements

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